1 The Application of Spatial Analysis to Coastal Environments

1.1 Geographical Foundations of Spatial Analysis

The use of quantitative techniques in geographical enquiry stems from a simple belief that, in many situations, numerical data analysis or quantitative theoretical reasoning provides an efficient and reliable means of obtaining knowledge about the world. Spatial analysis is often associated with quantitative geography, which evolved during the 1950s and 1960s as the increased availability of numerical data provided a basis for geographical reasoning. The quantitative revolution marked a major turning point in investigative methods, with a transition from a descriptive to an empirical geography (Livingstone, 1993; Inkpen and Wilson, 2013). Quantitative geography can broadly be defined as the development of spatial theory through analysis of numerical spatial data and the construction and testing of mathematical models of spatial processes (Fotheringham et al., 2000). From a philosophical viewpoint, it is often aligned with positivist perspectives that use empirical approaches to define laws pertaining to spatial processes. These often have the objective of explaining observations made about the natural world, or predicting its characteristics in space and time. Yet quantitative techniques do not provide a flawless argument. Indeed, it is precisely because of the need to account for error and uncertainty in both data collection and model formulation that statistical methods have come to dominate quantitative geography (Fotheringham et al., 2000). A common objective of many quantitative geographers is therefore to conduct analysis that maximises knowledge on spatial processes while simultaneously minimising error. Spatial analysis has advanced progress towards this objective over the last few decades, assisted by developments in technology such as remote sensing instruments and the global positioning system (GPS) and allied computational and statistical methods for analysing large spatially referenced datasets. The aim of this book is to explore the exciting foundation that such developments provide for analysing, and better understanding, coastal environments.

1.2 Definition of Spatial Analysis: Academic and Analytical Origins

Spatial analysis is defined as a collection of techniques and statistical models that explicitly use the spatial referencing associated with each data value or object under study (Upton and Fingleton, 1985; Fotheringham and Rogerson, 2013). The spatial sciences are largely based on empirical methods that involve making observations and collecting data about the natural world (Upton and Fingleton, 1985; Fotheringham et al., 2000). Spatial analysis is therefore clearly differentiated from non-spatial analysis.

The latter does not engage with the spatial referencing of data values but interrogates data points and associated trends regardless of their geographical distribution. Within this broad definition, several families of spatial analysis techniques can be defined, including exploratory and confirmatory spatial data analysis, geostatistics (or spatial statistics) and map algebra (Figure 1.1). It is also important to distinguish between spatial analyses that incorporate aspects of uncertainty, such as locational uncertainty, and those that do not, as these can influence the results of spatial statistical analyses (Cressie, 2002).

Spatial analysis has a role to play in supporting the search for scientific explanation. To this end, two families of spatial analytical techniques can be further differentiated as exploratory and confirmatory spatial data analysis. Exploratory spatial data analysis (ESDA) builds on methods of exploratory data analysis to investigate observable patterns in a given dataset (Tukey, 1977). This may involve identifying broad-scale trends, spatial clusters or outliers. ESDA is often a precursor to confirmatory spatial data analysis, which further evaluates datasets using traditional statistical tools of inference, significance and confidence limits to quantify the extent to which data observations could be expected to occur by chance alone, or because of some underlying process (Gelman, 2004). Confirmatory or inferential statistical methods therefore provide a basis for making statements (or inferring) about large populations of data samples on the basis of smaller ones. Where significant relationships are found, inference can then be used in a predictive manner to simulate values either into the future or across unsampled geographic areas. Spatial models can therefore be used as important tools for furthering our understanding of natural phenomena through explanation and prediction.

Spatial analysis has a more general role to play in problem solving because of spatial dependence. This is the phenomenon whereby observations close together in geographic space are more alike than those that are further apart. This generic property of many phenomena can be exploited in problem solving, often forming an important underpinning principle to spatial statistical or geostatistical analysis. This structured component of spatial dependence can be usefully employed as a statistical predictor in various geostatistical techniques, for example, interpolation methods such as kriging (see Chapter 6). Yet it also raises issues that make it difficult to apply classical (i.e. non-spatial) statistical techniques to a problem. This is because the spatial dependence introduces data redundancy and a departure from fundamental statistical assumptions, such as the independence of observations.

The techniques of map algebra, or cartographic modelling, provide another clearly distinguishable class of spatial data analysis that treats maps as datasets in their own right. Map-based operations are used to generate new maps, often through the application of simple algebraic manipulations. By overlaying multiple maps on top of each other, the analyst is able to implement logical conditions (AND, OR, XOR) through arithmetic operations (+, −, ×) to identify areas on the map that meet a range of user-specified criteria. For example, the condition 'AND' is implemented with the + operand. It is achieved by adding two maps together to identify the areas on a map that simultaneously satisfy a set of conditions on two or more variables (Arbia et al., 1998). By structuring a sequence of multiple arithmetical operations, it is possible to successively apply multiple criteria to interrogate the attributes associated with a given area as a basis for routines such as multi-criteria decision analysis (see Chapter 3) (Kitsiou et al., 2002).

Many frameworks of enquiry combine several different components of spatial analysis into a powerful and practical methodological framework. For example, interpolation may be used to convert discrete point samples of data to a continuous raster grid. Then each individual grid cell might have equations applied to it that were derived from confirmatory methods (e.g. autoregression) using a cellular automata approach before the resultant layer is manipulated alongside another layer using map algebra techniques. In this way, several different components of spatial analysis are brought together into a framework for investigating the natural world.

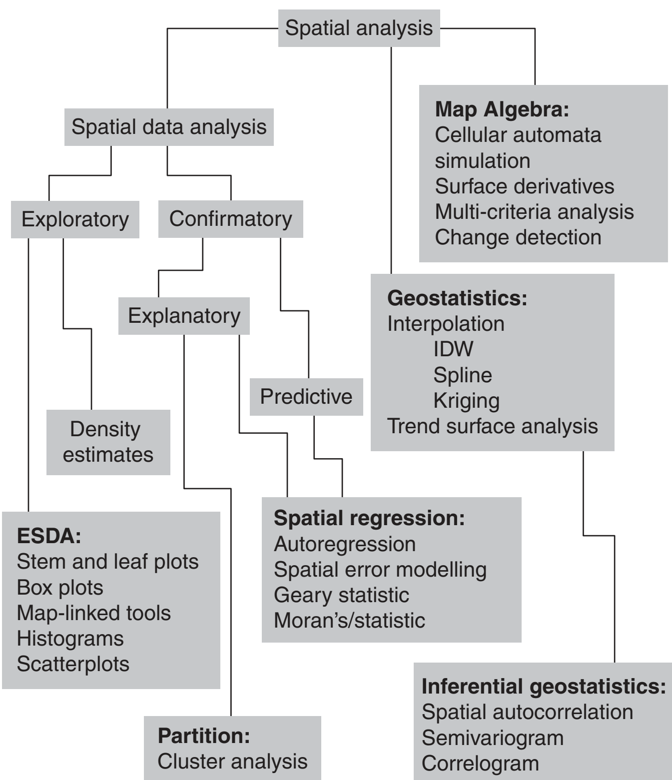

Figure 1.1 Taxonomy of the different types of spatial analysis described in the analytical chapters (Chapters 3, 5, 6 and 7) of this book. Boxes with bold headings represent established techniques; other boxes further up the taxonomy group these techniques by their analytical objectives.

1.3 Location Matters in Coastal Environments: Place and Space

A spatial analyst understands places by constructing explanations that draw on the ideas and methods of allied disciplines, including geology, biology, environmental science, oceanography, biogeography, landscape ecology or geomorphology (or some combination of these). One distinguishing feature of the environmental sciences, as opposed to many areas of experimental science, is that they are observational sciences. Outcomes have to be taken as they are found. The analyst is not usually in a position to test their ideas by experimenting with processes that they think may be important for a particular explanation. In terms of data, they cannot manipulate levels of explanatory variables (a variable being any characteristic, number or quantity that can be counted) or replicate outcomes. Nevertheless, an observational scientist is able to use information on location to induce variability in an explanatory variable as a form of 'natural laboratory'. Location can act in two distinct ways in this regard: location as *place* (and, by extension, context) and location as *space* (Haining, 2003).

Coastal environments are made up of a diverse array of places. Each of these places is subject to a unique set of local environmental conditions. In the context of spatial modelling, the treatment of location as 'place' draws on the diversity of places to vary the value of associated variables that may be of interest to the analyst. Consider the case of trace metals found in the mussels of the northwestern Mediterranean. A regional coastal survey measured levels of trace metals in mussels across stations at 15 different shoreline locations adjacent to urban areas with different levels of industrialisation (Fowler and Oregioni, 1976). The varying levels of industrial activity gave rise to measurable differences in levels of heavy-metal pollution into neighbouring coastal waters. This information can be combined with mussel population data to analyse the relationship between levels of water pollution in the direct vicinity of the mussel beds and the occurrence of trace metals in the soft tissue of these populations. In such an analysis, it is necessary to account for the effects of possible external confounding processes or variables that may correlate with the variables explicitly under consideration (e.g. mussel age, hydrodynamic mixing of the coastal waters, etc.). Highest trace-metal values were found in mussel tissue samples that were extracted from beds adjacent to port cities, and areas in the vicinity of river discharge. This indicates the importance of *place* as context for mussel beds along the coastline (Fowler and Oregioni, 1976). The effect of place can operate at a hierarchy of scales, from the immediate neighbourhood up to regional scales, and may include both contextual and compositional effects. For example, variation in trace-metal concentration might also be explained in terms of mussel age or the specific types of industrial development on the adjacent coastline (the compositional effect).

Gradients of different localised environmental conditions are discernible within coastal environments. The alternative 'space' view of location enters into explanation in the observational sciences by emphasising how objects are positioned *with respect to one another* along such gradients and how this relative positioning may enter explicitly into explanations of observable environmental variability. Such variability might arise from interactions between the places that are a function of those spatial relationships, and can be expressed through measurements such as distance, gradient and neighbourhood context. A gradient is a local property of a space that arises from the relative magnitude of a variable in two neighbouring areas (Burrough and McDonnell, 2011). For example, the levels of wave energy in a semi-exposed bay during a storm reflect the water depths and degree of exposure of a single location. But they also reflect the seafloor composition of neighbouring locations that determine wave energy through their capacity for frictional attenuation. Thus, the gradient between these two areas induces an effect in both locations that is not purely a consequence of the inherent properties of the two respective neighbourhoods. Rather, the instantaneous level of wave energy for a given location reflects the multiple paths along which the wave may have travelled to reach that location. Returning to the example of trace metals in the mussel beds of the NW Mediterranean, a *space* treatment of location might investigate the concentration of trace metals in mussel tissue as a function of the distance of individual mussels from the point of river discharge at an individual shoreline station. In a meta-analysis of the influence of local environmental conditions on the characteristics of 103 low-lying reef islands along the Great Barrier Reef (GBR), distance from the mainland coastline emerged as a strong predictor of island character. This reflected the variable sea-level history of each island across the sloping GBR shelf. A gradient of island age was inferred that corresponded to the length of time available for island evolution, with more evolved islands built up on higher platforms nearer the coastline than their younger seaward counterparts that had to build up from lower antecedent platforms (Hamylton and Puotinen, 2015). Finally, analyses that draw on the contextual surroundings of a given data point represent another family of contextual analyses that treat location as *space*. These include hydrological flow models that use slope information to map river flow through catchments, or the analysis of viewsheds that express visible areas accounting for the elevation of the neighbourhood surrounding a given location.

1.3.1 Examples of the Role of Place and Space Within Coastal Environments

Early work on coastal environments examined why different areas of the intertidal zone gave rise to distinct benthic community assemblages (Stephenson and Stephenson, 1949; Chapman and Trevarthen, 1953). More recently, spatially referenced datasets covering large geographic areas (e.g. 100 km × 100 km) provide consistent and synoptic information on physical and environmental characteristics of the coastal zone. These include digital elevation models extending from the terrestrial to the marine domain, and hydrodynamic models of wave power or current strength. They represent important sources of information on potential environmental explanatory variables. Confirmatory data analysis techniques draw on *location* to link data values that correspond to dependent and independent variables in overlapping datasets.

Changes to the way that humans use space within coastal zones have drawn attention towards the geographical variation of coastal development, including land-use transitions associated with expanding urban areas, and industries such as agriculture and aquaculture reclaiming riparian swamplands (Davies, 1972). More recently, coastal spatial datasets have provided a foundation for coastal vulnerability assessments that combine information from multiple sources to form an index of vulnerability to the various impacts that climate change can have on coastal environments. These include sea-level rise and the increased frequency and intensity of storms and cyclones. Vulnerability indices are often calculated from information on physical variables such as geomorphology, coastal slope, relative sea-level rise, shoreline erosion or accretion, tidal range, wave height, exposure and infrastructure (Gornitz, 1991; Gornitz et al., 1994; Abuodha and Woodroffe, 2010). They may also incorporate socioeconomic information, such as population, cultural heritage, roads, railways, land use and conservation status (McLaughlin et al., 2002). Thus, the development of vulnerability assessment tools, such as DIVA (Hinkel and Klein, 2009) and Smartline (Sharples et al., 2009), has provided a framework for integrating multiple datasets for an assessment of contextual vulnerability. This draws explicitly on a treatment of location as *place*.

Species distribution models (SDMs) correlate species occurrence with environmental data in geographic *space* to explain and predict the distribution of a given species of interest. Although SDMs were first applied in the terrestrial domain, they are increasingly being used in marine environments, where their success at constructing reliable explanations and predictions depends on unique physical properties of marine habitats and biological characteristics of marine organisms being accounted for. These properties include enhanced dispersal ability, species interactions and shifting environmental requirements throughout life-history stages (Robinson et al. 2011). Owing to both their commercial value and data availability, fish are often the focus of such models. These have practical value for planning marine protected areas and designating essential fish habitats, alongside permissible fishing zones (Leathwick et al., 2008; Valavanis et al., 2008; Maxwell et al., 2009). Maxwell et al. (2009) modelled the distributions of commercially harvested plaice, sole and ray in UK waters to inform conservation planning. Motivated by population declines due to habitat degradation and fisheries by-catch mortalities, models for marine mammals are also relatively common (Redfern et al., 2006; Panigada et al., 2008), particularly for informing habitat conservation (Bailey and Thompson, 2009). Ecological patterning of benthic organisms (those that live on the seafloor) has also been a common research focus, largely due to the distinctive distribution of features such as seagrass beds, coral patches and delta channels that are observable from aerial imagery.

1.4 Spatial Processes in Coastal Environments

Four generic spatial processes that are of particular significance in coastal environments are diffusion, dispersal, marine species interactions and environmental controls. These operate across a range of geographical and temporal scales.

1.4.1 Diffusion

Diffusion occurs when a substance undergoes a net movement along a concentration gradient (i.e. from high to low concentration). At any point in time, it is possible to specify in which areas the given substance is present, and in which it is not. Along the coastline, the presence of a water body often fundamentally influences the mechanism responsible for the spread (e.g. through tidally or wind-drive currents and waves). Such hydrodynamic influences will determine how the substance, such as an oil spill across the sea surface, diffuses and its rate of diffusion. The quantification of diffusion coefficients in coastal sediments has received substantive research focus in relation to contamination by pollutants and the associated practical implications of compromised groundwater quality, as also has the downward mixing of gases commonly found in the atmosphere and how this effects the distribution and population structure of sediment benthic invertebrate communities (Hyland et al., 1999).

1.4.2 Dispersal

Dispersal refers to the tendency for marine organisms to spread away from an existing population or site of origin (Kinlan and Gaines, 2003). The potential for dispersal is determined by the structure of the coastal environment and the method by which an organism disperses. Many marine organisms, including plants and benthic animals, either shed their reproductive propagules or have a pelagic larval stage during which their relatively small size allows them to disperse through a comparatively large and complex fluid environment, providing a potential for wide transport by currents (Kinlan and Gaines, 2003). In the marine environment, there are comparatively fewer physical barriers to dispersal than in the terrestrial environment (Steele, 1991). Physical barriers in the sea include continental and island land masses (Begon et al., 2006), ocean frontal systems and currents (Kinlan and Gaines, 2003), vertical stratification of the water column (Longhurst, 2010), changes in substrate and bathymetry (Gaines et al., 2007) and heavily polluted regions. Nevertheless, marine dispersal often occurs across large distances, sometimes at the scale of ocean basins; taxonomic studies suggest that the corals colonising the reefs of the west Indian Ocean were seeded by larvae originating from the Indo-Pacific region (Sheppard, 1998). Similarly, rates of range expansion in marine macroalgae far exceed those of terrestrial plants, and the distances that insects on land disperse are also generally lower on average than marine invertebrate and fish species (Kinlan and Gaines, 2003). Indeed, many marine organisms have been observed to disperse farther and faster than their terrestrial counterparts, which reflects the increased connectivity that results from a combination of the presence of a fluid medium and fewer barriers in marine systems than on land (Carr et al., 2003; Cowen and Sponaugle, 2009).

1.4.3 Marine Species Interactions

There are many different types of ecological interactions that could influence the spatial distribution of a given species, including competition, facilitation, parasitism, feeding (herbivory and predation), mutualism, symbiosis and disease (Robinson et al., 2011). These present both positive and negative influences on a given population. Competitive interactions are likely to be easier to include in models of benthic distributions as opposed to pelagic fish species because of the paucity of data on competitive exclusion in pelagic habitats (Bilio and Niermann, 2004). Path analysis and correlative species distribution models have been used to explore the relative influence of interspecific competition and the environmental correlate of temperature on barnacle distributions (Poloczanska et al., 2008). Multivariate population data have been used to test whether the presence of a dominant competitor mediated the climatic influence on the subordinate species. The influence of temperature has been shown to be significant for the dominant competitor, and only indirectly affected the abundance and distribution of the inferior competitor.

The relative importance of interactions and environmental conditions to marine species distributions is highly dependent upon the feeding behaviour of different organisms. In marine systems, the availability and density of prey may be an important factor in determining the distribution many apex predators (mammals, tuna and some sharks) that are less constrained by environmental conditions due to their ability to maintain body temperatures independently of surrounding environmental conditions (Torres et al., 2003; Redfern et al., 2006; Wirsing et al., 2007). By contrast, many benthic invertebrates cannot thermoregulate and tend to be opportunistic generalist feeders that consume a wide variety of prey suspended in the water column. Consequently, they are restricted more by ambient environmental conditions than by specific dietary requirements. In many cases, species interactions *per se* are difficult to represent as variables. Nevertheless, their spatial structure can be captured in models as interaction parameters that draw on statistical methods of characterising autocorrelation.

Organisms can aggregate because of biological processes that are separate from environmental ones, such food availability, predator or competitor avoidance, mating behaviour, limited dispersal and advection, that cause spatial autocorrelation (Ritz, 1994). Spatial autocorrelation refers to the correlation of a single characteristic as a function of its position in geographic space, such that characteristics at proximate locations tend to be more closely related than their distant counterparts. This fundamental property of most datasets arises because of processes that abide by Tobler's first law of geography: 'everything is related to everything else, but near things are more related than distant things' (Tobler, 1970). Positive spatial autocorrelation means that geographically nearby coastal features, such as the ecological composition of a littoral zone, tend to be similar because of spatially structured processes and neighbourhood interactions. If a spatially dependent species distribution model has greater explanatory success than its non-spatial counterpart, the theoretical implication that follows is that neighbourhood interactions play an important role. This invites greater consideration of interaction between sites, which can be captured by spatially explicit models.

1.4.4 Environmental Controls

The arrangement of individuals of a given species will be fundamentally dependent on the presence of environmental controls. For example, sea surface temperature and the presence of rocky reef habitat were found to be a major predictor of the spatial abundance of two abalone species in southern Australia (Mellin et al., 2012). Shorelines typically traverse a vertical series of littoral sub-environments that represent critical gradients in environmental conditions. Factors such as degree of aerial exposure, water submergence, salinity, wave exposure, temperature and light availability all vary along these vertical gradients (Harley and Helmuth, 2003). Across broader spatio-temporal scales, the configuration of geological foundations provides a first-order control on presence or absence of marine habitat.

1.5 When Is It Desirable to Conduct Spatial Analysis for Coastal Management and Research?

The presence of spatial autocorrelation in datasets introduces several deviations from the assumptions of classical statistics. These warrant attention in studies of coastal environments. Indeed, it is only through the application of spatial (as opposed to classical or ordinary) statistics that these deviations can be addressed (Haggett and Chorley, 1967). For example, where classic statistics are used, stationarity is assumed across a dataset. This corresponds to constant statistical characteristics (such as mean and covariance values of a measured property) across a study area. In coastal environments that are characterised by high levels of environmental variability and associated heterogeneity, such assumptions often fail to be met because of contextual processes that operate at a hierarchy of scales. Spatially dependent influences can only be detected using techniques that draw explicitly on the location of attributes in space to investigate structures within the data. For example, when attempting to explain or predict the variable communities that inhabit adjacent intertidal littoral zones, the presence of interactive (or neighbourhood-context) effects in ecological communities suggests a need for a spatial (as opposed to classic or non-spatial) model (Cliff and Ord, 1981). It is therefore often desirable to adopt a spatial approach to the analysis of data. While the presence of spatial autocorrelation presents an analytical challenge, there are a number of practical benefits that arise from its incorporation into the analysis of coastal environments. Discussed further in Chapter 6, these include:

- quantifying the extent and pattern of spatial dependence across coastal zones,
- signifying the presence of redundant information in field datasets,
- indexing the nature and degree to which fundamental assumptions of classic (i.e. non-spatial) statistical techniques are violated,
- indicating the nature (spatial vs non-spatial) of an observable pattern to be modelled, and
- offering an opportunity to partition out and utilise spatially structured components of model error as a surrogate for a missing variable.

Cambridge University Press
978-1-107-07047-9 — Spatial Analysis of Coastal Environments
Sarah M. Hamylton
Excerpt
More Information

1.6 Spatial and Temporal Scales of Analysis

Most coastal environments are subject to numerous interrelated processes that define the physical space within which patterns are observed and organisms or landforms such as beach spits interact. Process scales on coastlines can be expressed in terms of their operational spatio-temporal ranges (Figure 1.2). These scale ranges have been identified for numerous purposes relating to coastal environments, including assessment of climate change impact (Slaymaker and Embleton-Hamann, 2009), studying coastal morphodynamics (Cowell and Thom, 1994; Woodroffe, 2002) and landscape ecology (Forman, 1995). Within these spatio-temporal scales, physical characteristics such as rocks and sediments may be examined by geologists and geophysicists, living organisms may be described by biologists and ecologists, environmental processes may be explored by oceanographers, and human use of the coast may be analysed by economists, human geographers, planners or social scientists. The appropriate scale for conducting spatial analysis depends on the questions that are to be addressed, particularly the dimensions of a phenomenon or process under consideration and the delineation of corresponding process ranges. This can often be subjective. For example, if ‘water movement’ is considered to be an important process for the evolution of sandy islands, then relevant timescales encompass a wide range of variability. They might include glacially driven fluctuations in sea level (10^5 a), which fundamentally determine the time periods during which islands are able to evolve, or the passage of individual waves (1–10 s), which are significant determinants of modern sediment deposition (Gourlay, 1988). From a process-led perspective, it is therefore possible to delineate spatio-temporal scales at which associated features of interest can be studied. It is also important to align these scales of analysis with the operational scales of instruments used to gather information (e.g. mapping technology such as airborne or spaceborne remote sensing).

Figure 1.2 illustrates the overlapping ranges of spatio-temporal scales at which environmental processes operate (and are analysed) in coastal environments. A continuum exists between the small and large extremes, with process scales that overlap in extent, but within which distinct disciplinary focus ranges can often be delineated. On the one hand, a biologist may use a microscope to observe instantaneous physiological processes occurring within the cells of a marine organism at smaller spatio-temporal scales (in the lower left of the diagram). On the other hand, a geologist may collect fossil or rock evidence of past sea levels where shorelines were submerged in a previous interglacial period (in the upper right of the diagram). The dimensions corresponding to the scales at which the biological and geological ranges meet in the middle also coincide with the scales at which information is acquired from coastal environments. This is often referred to as the ‘landscape’ or ‘seascape’ scale. It represents a common scale at which map-based coastal spatial analysis is conducted. This is noteworthy because, in a disciplinary sense, coastal studies have hitherto tended to